ANALYSIS OF THE IMPACT OF SARS-COV-2 PANDEMIC PARAMETERS ON PHARMACEUTICAL COMPANY STOCK PRICES

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Citation:
Savchenko, V. (2025). Analysis of the Impact of SARS-COV-2 Pandemic Parameters on Pharmaceutical Company Stock Prices. *Economics, Finance and Management Review*, (2(22), 82–93.
https://doi.org/10.36690/2674-5208-2025-2-82-93

Received: June 02, 2025
Approved: June 29, 2025
Published: June 30, 2025

Abstract. *A company's share price today is influenced by numerous factors, including internal fundamentals, political decisions, industry-specific developments, macroeconomic conditions, and global trends. Investors face the challenge of choosing an appropriate approach to identifying target industries and assets, interpreting analytical results, and determining optimal market entry points. One such challenge has been the COVID-19 pandemic. Within this context, key issues arise regarding the prediction of share price movements for companies in the healthcare sector (Pfizer Inc., BioNTech SE, Moderna Inc., Merck & Co Inc., GSK plc.) listed on the stock exchange. This study investigates the influence of COVID-19 case data, transformed through various technical indicators, on the accuracy of share price forecasts. It identifies the specific tasks these indicators address and proposes a systematic framework for selecting and configuring technical analysis tools. The paper explores different methods of generating and interpreting signals from individual indicators and their combinations, emphasizing their relevance to forecasting asset price movements. Several criteria are introduced for evaluating the effectiveness of these forecasting methods during the testing phase. The study compares the outcomes of different forecasting system configurations, identifying the most effective ones based on predefined criteria. Using weekly stock data from 2020 to 2024, the research establishes the optimal combination of indicators for the forecasting system. Furthermore, it highlights potential areas for optimization and suggests additional tools for enhancing system performance. In conclusion, the study demonstrates the feasibility of the proposed forecasting approach for conducting real stock transactions involving the selected healthcare companies' shares. The practical value of the study lies in its demonstration that publicly available, non-financial data can be transformed into effective market forecasting tools. This has implications for investors, analysts, and portfolio managers seeking to enhance their decision-making frameworks during periods of global uncertainty. Moreover, the developed approach offers a flexible blueprint for adapting to future crises, where the speed of information processing and interpretation may determine the success of strategic financial decisions.*

Keywords: *COVID-19; quotes; technical indicator; moving average; simple moving average; oscillator; stock exchange; resource allocation; stock market; trading system.*

***JEL Classification**: G10, G17, H54*

Formulas: 3; fig.: 0; tabl.: 7; bibl.: 26

Introduction. In the wake of COVID-19, which continues to pose economic risks, the pharmaceutical industry has become increasingly vital for nations and the global economy. Its role extends beyond healthcare, influencing geopolitical strategies, public health security, labor markets, infrastructure development, and overall economic resilience. As such, the sector garners significant attention from investors, governments, and businesses.

Understanding trends in the stock prices of pharmaceutical companies is essential for stakeholders involved in resource allocation within the economy. For businesses, this knowledge guides decisions on funding strategies, research investments, and dividend policies. For investors, it provides a basis for assessing market sentiment and the potential growth prospects of companies, shaping decisions on investment or divestment. For governments, it offers critical insights into the industry's outlook and individual company performance, especially given that this essential sector may require targeted support during periods of economic uncertainty and turbulence.

The stock market represents a system where a large number of participants interact, shaping expectations regarding the true and fair value of assets traded on respective stock exchanges (Cullen, 2024), (Johnson, Tuckett, 2022). These expectations, their fluctuations, and the actions of participants driven by these expectations significantly influence market quotations. These expectations may relate not only to the operational parameters of a company itself but also to the external environment in which it operates. Although the COVID-19 pandemic is now considered to be under control, cases of infection with new variants continue to be recorded regularly (WHO, n/d), (Nesteruk, 2024), (Nesteruk, 2025). Consequently, the spread of COVID-19 remains a factor that can impact the performance of companies in the healthcare sector and the valuation of their assets on the stock market.

Accordingly, analyzing the rate of change in COVID-19 infection cases can provide stakeholders with the information necessary to make informed economic decisions related to the allocation of available resources. As part of our research, we will explore technical indicators as a tool for forecasting changes in a company's asset prices based on variations in infection rates.

Literature review. Existing research primarily focuses on analyzing or COVID-19 spread (Nesteruk, 2024), (Chumachenko et al., 2024), or the performance and volatility of assets or markets as a whole or examines the reaction of market participants to the news. However, it does not utilize specific epidemic-related parameters to forecast the direction of stock price movements for companies involved in producing COVID-19 vaccines. For example, Caiado, Lúcio (2023) evaluates the performance of different clusters of the US stock market during the COVID-19 pandemic using asymmetric GARCH models without including the pandemia's parameters in the model. As well as Padaria et al. (2023) estimate different machine-learning approaches related to local stock quotes prediction during the COVID-19 pandemic. Carlos, López (2022) investigates the performance of healthcare and pharmaceutical industries during the COVID-19 pandemic. Researchers propose new metrics for measuring portfolio risk, however they do not assess the correlation between disease incidence data and asset prices. They also highlight a significant fact that despite global challenges, certain niche sectors have experienced significant growth during the pandemic, with the pharmaceutical industry standing out as a key example. Even before the onset of COVID-19, this sector showed considerable growth potential, driven by positive evaluations, increasing demand for pharmaceutical products, and a rising rate of drug approvals by the Food and Drug Administration (FDA) in recent years. The pandemic has further accelerated this growth, providing the industry with new revenue streams. Empirical evidence underscores that vaccine administration is the primary method for controlling virus transmission, leading laboratories with approved vaccines to secure substantial sales agreements. Baker et al. (2020) employed newspaper cuttings and online articles to analyze the influence of infectious disease outbreak news on stock market fluctuations. Ray et al. (2024) offered the niche application of multivariate time-series forecasting by employing MBSTS models and M-TCN architectures to analyze the impact of investor opinions and news sentiment extracted from various sources on stock market behavior, particularly identifying the first upturn after lockdown and improving overall forecasting accuracy compared to benchmark methods. Baek et al. (2020) in their study focus more on the impact of the spread of COVID-19 (using daily number of COVID-19 cases) on stock market volatility. Wang et al. (2020) conducted a comparative analysis of VIX and EPU indexes to determine their relative effectiveness in predicting international stock market volatility during the COVID-19 pandemic. Albulescu (2021) acknowledges the significant increase in volatility within U.S. financial markets during the COVID-19 pandemic. His empirical research demonstrates that this volatility was primarily driven by two key factors: the number of new daily infection cases globally and within the United States and the escalating fatality ratio. Engelhardt et al. (2021) posit that trust in the government plays a crucial role in mitigating market volatility. Their findings indicate that increased levels of societal and governmental trust are associated with lower levels of uncertainty within the country's stock market.

To address this research gap, this paper investigates the predictive significance of chosen indicators, their settings, and combinations applied to the COVID-19 spread parameters and evaluates their effectiveness in delivering accurate forecasts of pharmaceutical company stock quotes.

Aims. The objective of this study is to determine the potential impact of COVID-19 cases on the stock prices of healthcare companies and to utilize this impact for optimal resource allocation by economic agents on the stock exchange.

Methodology. This paper utilizes traditional scientific methodologies to develop a forecasting system designed to optimize resource allocation. The approach combines analysis and synthesis for system design, along with comparison and compilation to benchmark results against conventional methods. Statistical techniques are applied to evaluate the performance of the proposed systems, while scientific support methods are employed to summarize findings and draw conclusions regarding the development of the forecasting system. Together, these methods identify challenges and opportunities for economic agents in designing a stock price forecasting system that enhances resource allocation efficiency.

The formulas for the calculation of the indicators are provided in Table 1.

Table 1. Formulas

Indicator	Formula
SMA	$$SMA_n = \frac{1}{n} \times \sum_{1}^{n} P_i \quad (1)$$
Oscillator	$$O = MA_a - MA_b \quad (2)$$

Notes: n — number of periods, over which indicator is calculated, P_i — asset quote in period i (in our calculations this will be the closing price), MA_a – moving average, calculated by the appropriate method based on the asset's quote in period a (in our calculations this will be the closing or opening price), MA_b – moving average, calculated by the appropriate method based on the asset's quote in period b (in our calculations this will be the closing or opening price).
Source: compiled by author based on: Murphy, 1999; Savchenko, Bobrov, 2024

To interpret changes in indicators as trading signals, we employed the Heaviside step function (Zhang, Zhou, 2021) in the next way:

$$S(x) = H(x) \quad (3),$$

where x – indicator or indicators combination:
- *for MA and oscillators it is a difference of values in the periods t-1 and t-2;*
- *for MA combinations it is a difference of short- and medium-term MA in the period t-1;*

S(x) – signal of indicator or indicators combination;
H(x) – Heavyside function:
- *H(x) = 0 if x < 0;*
- *H(x) = 1 if x >= 0*

Explanation:
1) If S(x) = 0, then sell;
2) Else – buy.

Results. We've analyzed stock quotes of five companies, the leading COVID-19 vaccines manufacturers, whose shares are listed on liquid stock exchanges and are available for trading (Table 2).

Table 2. Information about companies

Company	Rank by revenue	Ticker	Revenue, $ bln.	Market cap, $ bln.
Pfizer, Inc.	2	PFE	59.38	149.04
Moderna, Inc.	4	MRNA	5.08	13.11
Merck & Co., Inc	1	MRK	63.17	247.7
GSK plc	3	GSK	31.31	67.85
BioNTech SE	5	BNTX	3.04	26.83

Source: compiled by author based on: YahooFinance (n/d), Single Use Support (n/d)

Also, we've analyzed data about new COVID-19 cases from 05.01.2020 to 08.12.2024 (*WHO, n/d*).

We constructed various regression models in the initial stage to identify potential linear or nonlinear relationships between infection data and stock prices. However, none of the models proved to be statistically significant.

As a result, we adopted an alternative data processing approach by applying technical analysis indicators. In this study, data on new COVID-19 infections was interpreted using technical analysis indicators. A technical analysis indicator is a tool used to mathematically transform data over a specific time period. Functionally, indicators are categorized into volatility (non-trend) and trend indicators. The moving average (MA) is a trend indicator, while oscillators are classified as non-trend indicators. Moving averages smooth out data over a preset period, filtering out sharp movements and assisting analysts in identifying the direction of a trend. Oscillators, on the other hand, help detect potential zones where current values exceed or fall below average levels (Murphy, 1999; Cullen, 2024). This study applied these tools to establish potential correlations between signals generated by calculated indicators and actual stock price changes for the respective companies.

Approaches to indicator construction and simulations used in the study. To test the trading strategy built using technical indicators, the following considerations were taken into account:

1) all buy and sell signals must be binary to eliminate the possibility of human interpretation errors;

2) the strategy must generate results that exceed the potential returns of a buy-and-hold strategy for the respective asset during the modeling period;

3) the modeling should cover various time periods (Aronson, 2011).

The sequence of calculations in our study was as follows:

1) data for calculations, system development, and testing for each asset were split, allocating 80% for system construction (2020-2023 in our case) and 20% for validation (2023-2024 in our case), as is standard in time series analysis (Joseph & Vakayil, 2021). All calculations were performed using MS Office Excel;

2) next, the Simple Moving Average (SMA) was calculated using the formulas from table 2. Indicator values were computed for periods ranging from 2 to 27 (period = 1 week) based on opening and closing prices. The performance of each period was assessed to determine which best met the defined criteria. The selection criterion was the highest average value (Savchenko, 2023);

3) moving averages with short (up to 4 weeks) and medium (5-27 weeks) horizons that showed the best results during the construction period were selected. Combined systems were constructed using these moving averages, and their effectiveness was checked during the construction period;

4) oscillator was calculated using the approach described by Savchenko, Bobrov (2024). Specifically, the difference between short- and medium-term moving averages, which generated the maximum absolute result, was recalculated. Among the oscillators, the one that showed the best performance during the construction period according to the selected optimization criteria was chosen;

5) for steps 2, 3, and 4, the impact of time lags and signal inversion on the results was also examined;

6) trading simulations were conducted during the validation period using forecasting systems based on the best combinations of moving averages, oscillators, and their combinations;

7) based on the results of the calculations, conclusions were drawn regarding the feasibility or infeasibility of using the approach compared to the baseline "buy and hold" strategy.

The trading actions based on the signals were as follows:

1) When the indicator (or combination of indicators) signaled a price increase existing short positions were closed at the closing price of the respective trading week and a new long position was opened at the opening price of the following trading week;

2) When the indicator (or combination of indicators) signaled a price decrease existing long positions were closed at the closing price of the respective trading week and a new short position was opened at the opening price of the following trading week.

Model Construction. Models were constructed using moving averages. The results of modeling using moving averages on the test period are presented in Table 4 below.

Table 3. Results of strategies with selected MA, chosen for further calculations, in the test period

Ticker	Indicator	Lag	Is inverted	Result, $
PFE	SMA(10)	4	Y	64.92
PFE	SMA(11)	3	Y	63.54
PFE	SMA(3)	0	N	40.33
PFE	SMA(15)	0	Y	48.84
MRNA	SMA(16)	0	Y	467.09
MRNA	SMA(11)	4	Y	604.18
MRNA	SMA(3)	0	N	485.36
MRK	SMA(4)	1	Y	79.62
MRK	SMA(4)	2	Y	75.11
MRK	SMA(5)	0	Y	61.46
MRK	SMA(20)	2	N	22.04
MRK	SMA(26)	0	N	22.67
GSK	SMA(6)	4	Y	33.42
GSK	SMA(8)	3	Y	32.59
GSK	SMA(10)	4	N	19.98
GSK	SMA(14)	2	N	25.89
BNTX	SMA(5)	3	Y	560.45
BNTX	SMA(11)	4	Y	528.21
BNTX	SMA(3)	0	N	440.58
BNTX	SMA(17)	2	N	449.75

Notes: SMA – simple moving average, t – moving average period.
Source: compiled by author.

Using these moving averages, we constructed strategies with MA combinations and oscillators, compared received results with simple MA strategies. The best modeling results are shown in Table 4.

Table 4. Results of the best strategies for construction period

Ticker	Indiactor	Lag	Is inverted	Result, $	Mx	Std	Skew	Kurt	Min	Max	Mo	Me
PFE	MA(10)	4	Y	64,92	0,33	1,53	0,39	1,79	-3,94	6,27	-1,29	0,34
PFE	MA(11)	3	Y	63,54	0,33	1,53	0,41	1,77	-3,94	6,27	-0,56	0,27
PFE	SMA(3)	0	N	40,33	0,20	1,59	-0,02	1,58	-5,03	6,27	1,29	0,26
PFE	O(3-15)	0	N	38,58	0,20	1,56	0,11	1,90	-4,97	6,27	0,13	0,22
MRNA	MA(3+16)	4	Y	608,37	3,20	18,71	1,51	6,65	-62,15	98,48	-8,63	1,03
MRNA	MA(11)	4	Y	604,18	3,11	18,59	1,54	6,72	-62,15	98,48	-8,63	0,95
MRNA	MA(3)	0	N	485,36	2,37	18,24	1,58	7,22	-62,15	98,48	-3,63	0,88
MRNA	O(3-16)	0	N	629,62	3,44	19,02	1,46	6,31	-62,15	98,48	-7,03	0,79
MRK	MA(4)	1	Y	79,62	0,39	2,53	-0,02	0,50	-8,06	7,89	1,39	0,34
MRK	MA(4)	2	Y	75,11	0,34	2,50	0,00	0,60	-8,06	7,89	1,39	0,24
MRK	O(5-20)	2	N	22,04	0,12	2,52	0,28	0,67	-7,02	8,06	1,28	0,16
MRK	MA(26)	0	N	22,67	0,12	2,52	0,04	0,78	-7,08	8,06	-0,34	0,02
GSK	MA(6)	4	Y	33,42	0,17	1,05	-0,08	2,09	-3,71	4,53	0,00	0,20
GSK	MA(8)	3	Y	32,59	0,16	1,02	0,18	1,68	-3,17	4,53	0,00	0,16
GSK	O(14-10)	4	N	19,98	0,11	1,01	0,34	1,57	-2,94	4,53	0,73	0,03
GSK	O(14-10)	2	N	25,89	0,13	1,00	0,43	1,54	-2,31	4,53	0,47	0,10
BNTX	MA(5)	3	Y	560,45	2,79	17,13	1,57	6,13	-62,09	86,38	-8,50	0,35
BNTX	MA(11)	4	Y	528,21	2,74	17,43	0,56	6,54	-86,38	78,69	0,35	0,62
BNTX	MA(3)	0	N	440,58	2,15	17,06	0,23	7,09	-86,38	78,69	8,50	1,08
BNTX	MA(17)	2	N	449,75	2,38	17,67	1,09	6,02	-62,09	86,38	-0,35	0,17

Notes: MA – simple moving average, O – oscillator, MA(t) – MA period, MA($t+t_1$) – combination of MA of related time periods, O($t-t_1$) – oscillator of MA of related time periods, Mx – average result, Skew – skewness of the result, Kurt – kurtosis of the result, Mo – mode of the result, Me – median of the result, Std – standard deviation of the result.
Source: compiled by author.

A comparison of our results to those of the 'Buy and hold' method, displayed in Table 5.

Table 5. The result of the "Buy and hold" strategy for construction period

Ticker	Entry date	Entry price	Exit date	Exit price	Result, $
PFE	05.01.2020	39.45	07.01.2024	29.44	-10.01
MRNA	05.01.2020	18.70	07.01.2024	111.04	92.34
MRK	05.01.2020	87.05	07.01.2024	117.22	30.17
GSK	05.01.2020	46.42	07.01.2024	39.21	-7.21
BNTX	19.01.2020	34.00	07.01.2024	111.66	77.66

Source: compiled by author

As we can see in Table 6, the "Buy and hold" strategy is not profitable on the construction period for all companies. For those assets where it generates profit, it is lower compared to most of the selected strategies, except:

1) MRK, O(5-20);
2) MRK, SMA(26).

Strategy verification. Four strategies were employed to verify the models for each instrument. Two strategies followed the trading signal directly, while the other two implemented the opposite of the signal. If we are wrong and COVID-19 data has no impact on stock quotes, verification will show negative results. Otherwise, we will get approval that at least one of the chosen strategies could be used in real stock market operations. The verification results of the selected trading strategies are shown in Table 6.

Table 6. Verification results

Ticker	Period	Lag	Is inverted	Result, $	Mx	Std	Skew	Kurt	Min	Max	Mo	Me
BNTX	3	0	N	44.38	0.91	6.60	2.16	11.46	-13.41	33.46	-0.33	0.51
BNTX	5	3	Y	-2.04	-0.04	6.59	-2.30	12.49	-33.46	13.41	0.33	0.3
BNTX	11	4	Y	-18.14	-0.36	6.58	-2.48	12.04	-33.46	11.12	0.33	0.17
BNTX	17	2	N	21.10	0.43	6.64	2.43	11.69	-11.12	33.46	-0.33	0.03
GSK	6	4	Y	0.00	0.00	1.02	0.65	1.44	-2.3	3.2	-0.04	-0.01
GSK	8	3	Y	-1.42	0.03	1.02	0.49	1.38	-2.3	3.2	-0.04	0.06
GSK	O(14-10)	2	N	-11.44	-0.23	1.01	-0.05	1.44	-3.2	2.44	-0.04	-0.07
GSK	O(14-10)	4	N	-11.14	-0.23	1.01	0.19	1.66	-3.2	2.44	0.34	-0.14
MRK	4	1	Y	23.12	0.47	3.30	0.71	0.97	-6.22	10.58	0.4	0.42
MRK	4	2	Y	33.86	0.69	3.26	0.61	0.92	-6.22	10.58	-	0.73
MRK	26	0	N	-13.08	-0.27	3.33	0.48	1.54	-7.87	10.58	1.04	0.4
MRK	O(5-20)	2	N	-23.73	-0.48	9.68	-0.07	5.43	-35.39	34.2	-	-0.79
MRNA	3	0	N	-69.69	-1.42	9.59	-0.08	5.60	-35.39	34.2	3.11	-0.78
MRNA	11	4	Y	48.89	1.00	9.64	-0.49	5.75	-35.39	34.2	-3.11	1.01
MRNA	O(3-16)	0	N	-17.83	1.55	9.57	-0.63	6.15	-35.39	34.2	-3.11	1.87
MRNA	MA(3+16)	4	Y	76.17	-0.36	9.69	-0.28	5.39	-35.39	34.2	-3.11	0.42
PFE	3	0	N	1.73	0.04	0.78	-0.38	1.08	-2.37	1.9	0.84	0.01
PFE	10	4	Y	8.97	0.18	0.76	0.51	0.58	-1.22	2.37	0.84	0.23
PFE	11	3	Y	11.65	0.24	0.74	0.38	0.69	-1.22	2.37	0.84	0.26
PFE	O(3-15)	0	N	0.79	0.02	0.78	-0.43	1.04	-2.37	1.9	0.84	0.08

Source: compiled by author.

Thus, our analysis has shown that:

1) for BNTX stocks:

a) the feasibility of using the SMA(3) without signal reversal or lag with a result of $44.38 USD/share is cinfirmed;

b) SMA(17) without signal reversal but with 2 periods lag with a result of 21.10 USD/share is confirmed;

2) for GSK stocks:

a) the feasibility of using the SMA(6) with signal reversal and 4 periods lag with a result of $0.00 USD/share is confirmed (compared to Buy&Hold strategy, will be shown below);

b) the feasibility of using the SMA(8) with signal reversal and 3 periods lag with a result of $1.42 USD/share is confirmed;

3) for MRK stocks:

a) the feasibility of using the SMA(4) with signal reversal and 1 period lag with a result of $23.12 USD/share is confirmed;

b) the feasibility of using the SMA(4) with signal reversal and 2 periods lag with a result of $33.86 USD/share is confirmed;

4) for MRNA stocks:

a) the feasibility of using the SMA(3) and SMA(16) combination with signal reversal and 4 periods lag with a result of $76.17 USD/share is confirmed;
b) the feasibility of using the SMA(11) with signal reversal and 4 periods lag with a result of $48.89 USD/share is confirmed;
5) for PFE stocks:
a) the feasibility of using the SMA(3) without signal reversal or lag with a result of $1.73 USD/share is confirmed;
b) the feasibility of using the SMA(10) with signal reversal and 4 periods lag with a result of $8.97 USD/share is confirmed;
c) the feasibility of using the SMA(11) with signal reversal and 3 periods lag with a result of $11.65 USD/share is confirmed;
d) the feasibility of using the oscillator (difference of SMA(3) and SMA(15)) without signal reversal or 4 lag with a result of $8.97 USD/share is confirmed.

A comparison of our results to those of the 'buy and hold' method during verification period, displayed in Table 7

Table 7. The result of the 'Buy and hold' strategy for verification period

Ticker	Entry date	Entry price	Exit date	Exit price	Result, $
PFE	07.01.2024	28.32	15.12.2024	25.57	-2.75
MRNA	07.01.2024	110.74	15.12.2024	41.77	-68.97
MRK	07.01.2024	117.59	15.12.2024	102.00	-15.59
GSK	07.01.2024	39.29	15.12.2024	33.95	-5.34
BNTX	07.01.2024	111.66	15.12.2024	120.38	8.72

Source: compiled by author

As we can see in Table 6, the 'Buy and hold' strategy is not profitable on the construction period for all companies, except BNTX.

Also, we would like to mention that strategies verification has shown one important point: among all assets, the strategies that consistently achieved the highest mean and median returns during the construction period produced the superior results.

Taking to account this finding, compared to the best indicators strategies, the results can be interpreted as:

1) for the PFE stock, the best strategy for the construction period (Mx = 0.33, Me = 0.34) is SMA(10) with signal inversion and 4 periods lag. The result of the verification period is $8.97/share – more than -$2.75/share "Buy and hold" strategy result;

2) for the MRNA stock, the best strategy for the construction period (Mx = 3.20, Me = 1.03) is SMA(3) and SMA(16) combination with signal inversion and 4 periods lag. The result of the verification period is $76.17/share – more than -$68.97/share "Buy and hold" strategy result;

3) for the MRK stock, the best strategy for the construction period (Mx = 0.39, Me = 0.34) is SMA(4) with signal inversion and 1 period lag. The result of the verification period is $23.12/share – more than -$15.59/share "Buy and hold" strategy result;

4) for the GSK stock, the best strategy for the construction period (Mx = 0.39, Me = 0.34) is SMA(6) with signal inversion and 4 periods lag. The result of the

verification period is \$0.00/share – but it is anyway more than -\$5.34/share "Buy and hold" strategy result;

5) for the BNTX stock, the best strategy for the construction period (Mx = 2.15, Me = 1.08) is SMA(3) without signal inversion or lag. The result of the verification period is \$44.38/share – more than \$8.72/share "Buy and hold" strategy result.

Based on these results, indicator strategies can be considered as providing effective resource allocation.

Discussion. The findings of this study demonstrate the potential of utilizing technical analysis indicators, based on COVID-19 case data, to forecast the price movements of pharmaceutical company stocks. While initial attempts to apply linear or nonlinear regression models proved statistically insignificant, the transformation of epidemiological data into trading signals via moving averages and oscillators provided meaningful insights. This shift from traditional statistical modeling to technical indicators underscores the complexity and nonlinearity of stock market dynamics, particularly during periods of heightened uncertainty such as the COVID-19 pandemic.

A key observation is that no universal strategy could be applied across all companies analyzed. The effectiveness of specific moving averages, oscillators, and their combinations varied not only between companies but also across different pandemic phases. This heterogeneity confirms that investor perception, market behavior, and company-specific fundamentals collectively influence how pandemic-related information is priced into stock values. Consequently, the individualized calibration of forecasting models is essential, reinforcing the need for tailored approaches in investment strategy development.

In the validation phase, several strategies outperformed the "buy and hold" approach, which often resulted in losses or marginal gains. Notably, the forecasting models for MRNA and BNTX stocks, built upon signal inversion and optimal lag periods, yielded substantial returns. This suggests that certain companies' stock prices were more sensitive to pandemic data transformations than others—possibly due to their core involvement in vaccine development and public visibility during the crisis. Conversely, companies like GSK and MRK exhibited more stable, less reactive behavior, indicating that broader company operations or investor profiles may dilute the impact of short-term pandemic indicators.

An important methodological contribution of this research is the use of the Heaviside step function to binary-encode trading signals, minimizing subjectivity and enhancing reproducibility. This technique offers a scalable framework for signal interpretation, which is critical when transitioning from academic modeling to practical trading applications. Furthermore, the alignment between construction-period performance metrics (e.g., mean and median returns) and validation-period outcomes reinforces the robustness of selected indicators. This finding supports the hypothesis that high-performing strategies during the modeling phase can serve as reliable predictors for future performance, at least in comparable market conditions.

Despite these strengths, the study has limitations. The selected technical indicators, while effective, do not account for other influential factors such as investor sentiment, macroeconomic indicators, or governmental policy interventions, which may amplify or suppress market responses to pandemic data. Additionally, the timeframe of analysis coincides with a period of high market volatility and frequent structural breaks, which may not be replicable in future health crises or economic cycles. The generalizability of the results beyond the context of COVID-19 also warrants cautious interpretation.

Overall, the research offers a novel perspective on the application of epidemiological data in financial forecasting. It contributes to both financial and public health analytics by demonstrating that even non-economic data, when appropriately transformed, can yield actionable insights for economic decision-making. Future developments could incorporate automated algorithmic trading systems, enhanced by machine learning, to dynamically adapt forecasting models as new data emerges. Moreover, exploring the long-term implications of persistent health shocks, such as long COVID, on investor behavior and asset valuation remains an important area for continued investigation.

Conclusion. Although the analysis of market and asset behavior before, during, and after the COVID-19 pandemic period has been covered in numerous studies, the relationship between pandemic parameters and changes in the stock prices of pharmaceutical companies has been scarcely investigated. Based on the conducted research, the author determined that a forecasting system for stock price changes of relevant companies, built on the analysis of pandemic parameters using technical analysis indicators, can be employed by economic agents for efficient resource allocation.

The conducted research provides the basis for the following conclusions:

1) the parameters of COVID-19 spread, analyzed using technical analysis indicators, can currently be used to forecast changes in the stock prices of pharmaceutical companies producing COVID-19 vaccines;

2) when processing data, it is necessary to consider signal inversion and the time lag with which changes in pandemic parameters affect stock prices;

3) the list of indicators, their combinations, inversions, and time lags must be tested separately for each asset. Universal settings cannot be applied;

4) one reason for this is that the prospects of different companies, even within the same industry, are perceived differently by stock market participants. This perception depends not only on company performance but also on fundamental factors. Accordingly, economic agents place stock market orders with varying durations and execution volumes to achieve their goals, which immediately impacts stock prices.

Accordingly, possible directions for further research are:

1) an analysis of methods for forecasting pandemic parameters (Chumachenko D. et al., 2024) and, consequently, the opportunities they provide for predicting changes in stock prices of companies in the respective sector;

2) the automation of calculations using any programming languages available to researchers, as well as the development of machine learning algorithms based on the author' proposed algorithm;

3) an analysis of possible impact of long COVID-19 syndrome on stock quotes of healthcare companies (Chumachenko D. et al, 2025).

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